Journal of Agricultural and Resource Economics 45(1):124–144 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.298438

Investigating Consumer Participation Decision in Community-Supported Agriculture: An Application of Cumulative Prospect Theory

Shuoli Zhao and Chengyan Yue

Using the framework of cumulative prospect theory (CPT), we investigate consumers' decision to participate in community-supported agriculture (CSA) under risk and uncertainty. We analyze discrete choice experiment data using a CPT framework that allows for flexible reference points and individual preference heterogeneity. Comparison between model specifications suggests that the CPT model with the control of all risk parameters generates better goodness of fit than the expected utility model. Market sensitivity analysis further indicates that, while CSA operators benefit from transferring production risk partially to consumers, the level of transferred risk has a great impact on market share.

Key words: CSA, discrete choice experiment, risk and uncertainty

Introduction

Community-supported agriculture (CSA) has become a primary marketing channel for local fresh produce, connecting producers and consumers directly in urban areas (Vassalos, Gao, and Zhang, 2016). CSA producers achieve increased profitability by avoiding market intermediaries and improved financial stability given that consumers make up-front subscription payments prior to the production cycle. Meanwhile, CSA consumers receive fresh, local produce throughout the growing season and the added benefits of enhanced community connection and support for sustainable agriculture.[1] Reflecting its status as an affordable and convenient alternative agricultural marketing channel that provides mutual benefits to producers and consumers, CSA programs have expanded rapidly over the past 30 years. According to the U.S. Department of Agriculture (USDA), the first CSA operation started in 1986, and there were 60 CSA farms in 1990. Over time, CSA programs gradually became popular, expanding to 1,000 participating farms by the early 2000s (U.S. Department of Agriculture, 2014) and increasing to 12,617 farms in 2012 (U.S. Department of Agriculture, 2014). The CSA model is expected to continue to grow (Vasquez et al., 2017).

Despite the favorable attributes, a major challenge for marketing CSA to new members and increasing the retention rate of existing members is risk and uncertainty in product yields. By participating in CSA membership, consumers have to pledge support and partner with a local farm

Shuoli Zhao is a research assistant professor of Agricultural and Applied Economics in the Division of Applied Social Sciences at the University of Missouri, Columbia. Chengyan Yue (yuechy@umn.edu) is a professor and the Bachman Endowed Chair in Horticultural Marketing in the Department of Applied Economics and the Department of Horticultural Science at the University of Minnesota, Twin Cities.

We greatly appreciate editor Miljkovic and two anonymous reviewers for their helpful comments and suggestions that improved the paper.

Review coordinated by Dragan Miljkovic.

[1] Other added benefits may include (but are not limited to) generating a community-friendly farm for people to participate in food production and pick up their own food, serving as an outdoor classroom for children and students to learn about agriculture, encouraging awareness of environmental protection around local communities, and supporting local farmers.

operation, sharing the risks of loss and possibility of gains in food production (Ernst and Woods, 2013). Therefore, purchasing CSA shares directly associates with both risks of loss and benefits of bonus gain. In a survey of 205 CSA producers, Woods et al. (2009) found that nearly one in three (29%) did not produce all the anticipated products in their shares, while 26% achieved overproduction and gifted excess produce to their customers.[2] However, to our knowledge, Bernard, Bonein, and Bougherara (2016) is the only empirical work to consider both preferences for risks and product attributes of CSA; their elicitations of risk preferences and product attribute preferences were carried out separately, which would cause an upward bias for both estimations. Unlike previous consumer studies on CSA, we integrate risk preference elicitation into the estimation of CSA arrangement attributes so that all major determinants of the decision to participate in a CSA program can be simultaneously identified and compared.

Risk preference has been a focal point of consumer studies for several decades, especially after the underlying axiom of expected utility theory (EUT) was challenged (e.g., Allais paradox, Kahneman and Tversky, 1979; equity premium puzzle, Benartzi and Thaler, 1995). To adequately describe individual decision making under risk and uncertainty, the most recognized non-EUT framework Tversky and Kahneman's (1992) cumulative prospect theory (CPT), which comprehensively explains consumers' behaviors of purchasing CSA shares compared to EUT. For example, contrary to the EUT, which assumes consumer preference depends on absolute levels of wealth, CPT argues that the perceived outcome depends on changes in wealth, as gain and loss, relative to a reference point. Once the reference point is defined, loss aversion is further assumed so that the steepness of loss function relative to the steepness of gain function is greater than 1. For CSA participations, consumers are likely to weigh the value of the final product by comparing it to the subscription price, which can be straightforwardly defined by the up-front payment. Loss occurs when the final product is worth less than the up-front payment, and gain takes place when the final product is worth more than the upfront payment. Given the same magnitude of loss and gain, loss hurts CSA consumers more than gain pleases them (Bernard, Bonein, and Bougherara, 2016). CPT also proposes that individuals tend to overvalue low probabilities of risk and undervalue intermediate and high probabilities, so the utility outcome is evaluated by weighted probabilities instead of objective probabilities. Probability weighting offers additional insights on the possible cause of low retention rates in CSA operations given the significant probability of risk.

For risk-preference analysis using the CPT framework, most prior studies consider a single-attribute domain such as money (e.g., Booij, van Praag, and van de Kuilen, 2010), health (e.g., Bleichrodt and Pinto, 2000) or time (e.g., Abdellaoui and Kemel, 2014). Meanwhile, consumer preferences for products with multiple attributes are generally studied in isolation from risk-parameter elicitations, even if product attributes contain risky prospects (e.g., Hayes et al., 1995). However, when conducting consumer preference analyses for products under risk and uncertainty, significant correlations between the preferences for product attributes and preferences for risks have been identified (Mitchell, 1999). For example, Jindal (2015) tested consumer preferences for attributes of extended warranties for washing machine under varying levels of risks and found that risk parameters and product attributes are mutually controlled and that CPT is relatively superior to EUT in analyzing consumer preferences for extended warranties. Therefore, to understand consumer purchasing decisions for CSA shares, we apply a discrete choice experiment (DCE) under the CPT framework to simultaneously elicit heterogeneous preferences for risks and attributes.

Specifically, we structurally incorporate CPT parameters—reference dependence, diminishing sensitivity, loss aversion, and probability weighting—into a DCE design with CSA attributes (including price, variety of produce, and pick-up distance), which allows simultaneous estimation for both product attribute preference and risk preference to avoid potential overestimation under separate elicitations. This model also allows for preference heterogeneity among target variables and flexible reference points that are individual- and choice-specific. Methodologically, the adopted

[2] Meanwhile, Woods et al. (2009) reported that 62% of producers surveyed sell excess produce through farm markets and 41% donate to food banks.

Table 1. Designed Characteristic Levels in the Choice Experiment for Eliciting Product and Risk Preferences

Characteristics	Explanation	Levels
Up-front payment	Total price for a 20-week representative CSA subscription	\$400 \$500 \$600
Number of product varieties	Number of average product varieties received in each subscription	Fair, 6–10 varieties Good, 11–15 varieties
Distance to pick-up location	Distance to the nearest CSA pick-up location from your work place or home	5 miles 10 miles
Chance of loss due to poor harvest	Probability (in percentage) that you will receive produce at a value less than what you have paid for due to uncontrolled factors	0%–80%, at 5% intervals, plus 100%
Chance of getting bonus produce due to good harvest	Probability (in percentage) that you will get bonus produce at the value that is higher than what you have paid for due to good harvest	0%–80%, at 5% intervals, plus 100%
Value of loss due to poor harvest	In case of poor harvest, how much monetary value will be lost from the total up-front payment	−\$50 −\$100 −\$150
Value of bonus produce due to good harvest	In case of good harvest, how much monetary value will be gained additional to the up-front payment	\$50 \$100 \$150

structural framework in this study is applicable for analyzing risk preferences for multi-attribute consumer products under CPT; previous risk preference elicitation methods use only monetary characteristics (e.g., lottery) (e.g., Abdellaoui, Bleichrodt, and L'Haridon, 2008; Tanaka, Camerer, and Nguyen, 2010; Bocquého, Jacquet, and Reynaud, 2014). Empirically, this study is the first combined evaluation of attribute and risk preferences for CSA. We draw important conclusions about marketing implications for CSA operators.

Experimental Design

Attribute

Table 1 summarizes the attributes and their associated variations. For product attributes, recent CSA studies show that product variety and pick-up distance are the major purchasing considerations. Adam (2006) stated that the variety of produce is the key attribute for overall satisfaction among CSA shareholders. Using online survey data, Vassalos, Gao, and Zhang (2016) confirmed that variety was among the top factors that affected CSA subscription. Paul (2015) also highlighted the importance of crop variety in minimizing farm production risks, and Connolly and Klaiber (2014) identified a significant premium associated with CSA programs' off-site delivery and convenient pick-up locations. Specifically, additional miles to the pick-up location from the metro area is associated with a decrease in CSA share prices. Similarly, Burnett, Kuethe, and Price (2011) reported a positive correlation between shorter distance and higher price premium among CSA programs. Combining previous literature and our interview with a small group of consumers, we include up-front payment, number of product varieties, and distance to pick-up location as product attributes in the choice experiment.

Our choice of price levels ($400, $500, $600) is based on the findings of the previous literature. Using a survey of 453 CSA programs, Connolly and Klaiber (2014) reported an average price of around $520 for a 20-week subscription, with a standard deviation of $136. Khanal (2016) analyzed share prices of 466 CSA programs and found an average weekly price of $26.9. Chase (2007) used $560 and $350 as the base prices for organic and regular 20-week subscriptions.

To elicit risk preference in CPT framework using DCE design, we incorporate risk attributes, including the chance of loss due to poor harvest, the chance of getting bonus produce due to good harvest, the value of loss due to poor harvest, and the value of bonus produce due to good harvest. We choose loss and gain levels ($50, $100, $150) based on a reasonable and acceptable range of ratios for variations in up-front payment (8.3%–37.5%). To capture the full scope of probability perception, we allow the hypothetical loss and gain probabilities to range from 0% to 80% at 5% intervals and include 100% probability to account for a purchasing decision made with certain gain or loss. The systematic distortions of individual probability perception are assumed to have opposite directions toward low probabilities versus medium-to-high probabilities with a reflection point (Tversky and Kahneman, 1992; Prelec, 1998). To make sure that our estimates of probability-weighting parameters are not driven by parametric assumptions, higher percentages of risk and uncertainty (>50%) within the full interval of 0 to 1 must be included in the choice experiment (Lusk, Schroeder, and Tonsor, 2014; Jindal, 2015).

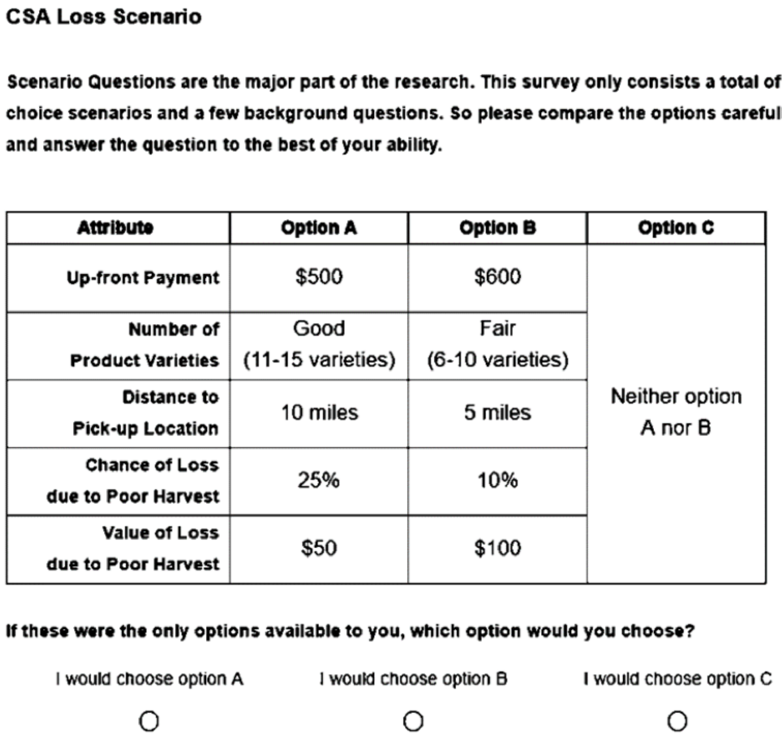
Choice Experiment Design

We adopt a choice experiment design to decompose CSA into its major product and risk attributes. DCE has been applied to a wide range of consumer preference topics such as the acceptance of neoteric products (Yue, Zhao, and Kuzma, 2015), willingness to pay for food attribute improvements (Lusk and Schroeder, 2004), health-related decision analysis (de Bekker-Grob, Ryan, and Gerard, 2012), and public perceptions of environmental policies (Hanley, Wright, and Adamowicz, 1998).

Given the large number of possible CSA choices with three major product attributes ($2 \times 2 \times 3 \times 18 \times 4 = 864$) using a full factorial design for DCE,[3] randomly assigning choice tasks with uncertainty attributes might produce less-than-desirable results (Roberts, Boyer, and Lusk, 2008). Using JMP® 8 software (SAS Institute Inc., Cary, NC), we selected 24 unique choice scenarios to achieve the highest D-efficiency (81.00 for overall design and 93.78 for product attribute design) while preventing risk-dominant choice. In each choice scenario, respondents choose between two CSA options with varied attribute profiles and an opt-out option. With the generated choice scenarios, we designed two survey versions by randomly assigning a block of 12 choice scenarios under possible loss in the first version and possible gain in the second. Respondents were informed that (i) if the potential loss or gain does not occur, then the actual value of product received from a CSA farm is equal to the up-front payment value, and (ii) besides the variations in the major attributes, all other characteristics are identical across CSA options (e.g., farmers' background, production practice, product freshness, size of share). Figure 1 shows an example of choice scenarios under possible loss.

Answering 24 choice scenarios could possibly cause a certain level of fatigue among respondents. To ensure the quality of responses, we adopted several strategies. First, to make sure the respondents fully understand the mechanism of CSA before answering discrete choice questions, we provided general information about CSA and explanations of all product and risk attributes. Then we presented a multiple-choice question to test respondents' knowledge about CSA; only those who answered the question correctly could proceed to the choice questions. Second, all questions were presented in a randomized order to avoid order effect. Third, to avoid fatigue, we

[3] The number of possible CSA options is calculated based on two distance levels, two product variety levels, three up-front payment levels, 18 risk probabilities, and four possible outcomes of loss and gain (including no loss or gain).



CSA Loss Scenario

Scenario Questions are the major part of the research. This survey only consists a total of 24 choice scenarios and a few background questions. So please compare the options carefully and answer the question to the best of your ability.

Attribute	Option A	Option B	Option C
Up-front Payment	\$500	\$600	Neither option A nor B
Number of Product Varieties	Good (11-15 varieties)	Fair (6-10 varieties)	
Distance to Pick-up Location	10 miles	5 miles	
Chance of Loss due to Poor Harvest	25%	10%	
Value of Loss due to Poor Harvest	\$50	\$100	

If these were the only options available to you, which option would you choose?

I would choose option A ○ I would choose option B ○ I would choose option C ○

Figure 1. Screenshot of Discrete Choice Scenario Example in Possible Loss Circumstance

added time screening, which excludes respondents who take less than 6 seconds to comprehend and answer each choice scenarios. Fourth, we randomly inserted two screening choice questions directing respondents to choose a specific choice regardless of CSA profiles in each DCE block to screen those who were inattentively answering the survey. Fifth, following Chung, Boyer, and Han (2011), we pretested the survey instrument with 50 respondents to verify that both functional forms of CPT and EUT were estimable under the designed number of options and choice sets. Last, the survey contained only DCE questions and self-reported sociodemographic questions, which greatly shortened the overall length of the survey and decreased the possibility of survey fatigue.

Methodology

Utility Index, Value Function, and Probability Weighting

With the experimental design of our discrete choice scenario, consumers choose between $J = 3$ options (2 CSA options, 1 opt-out option) for $S = 24$ scenarios (12 for possible loss, 12 for possible gain). Each option is characterized by three product attributes (up-front payment price, p_{js}; product variety, n_{js}; distance to pick-up location, d_{js}) and two risk attributes (percentage of poor or good harvest, π^-_{js} or π^+_{js}, and value of loss or gain, p^-_{js} or p^+_{js}). We define a vector space, $\boldsymbol{x}_{js} = (p_{js},\ n_{js},\ d_{js})$, representing product attributes. Given consumer heterogeneous preference, which is measured by the parameter vector $\boldsymbol{\theta}_i$, if consumer i chooses CSA option j in scenario s, the deterministic utility index $y^{\pm}_{ijs} = y(\boldsymbol{x}_{js}|\boldsymbol{\theta}_i)$ can be defined as

$$y^{\pm}_{ijs} = c_{ij} + n_{js-i}\beta_i + d_{js-i}\gamma_i - p_{js-i}\delta_i, \quad (1)$$

where c_{ij} is the CSA-specific constant subject i obtained from buying CSA option j in scenario s. Utility c_{ij} measures the additional benefits from purchasing CSA share that are not covered by the product attributes included in the choice experiments, which might include local and quality-assured food, increased involvement in local community, and satisfaction from supporting local sustainability. Parameters β_i and γ_i are coefficients for variety and distance, respectively, and δ_i is the coefficient for price.

There is a possibility that a monetary loss will occur from the final product; the consumer could receive his/her CSA subscription box with a value lower than the up-front payment. In this case, if consumer 's choice of CSA option j in scenario s results in a loss of p_{js}^-, then the utility index of loss y_{ijs}^- is defined as

$$y_{ijs}^- = \eta_{ij}^- + p_{js}^- \delta_i, \tag{2}$$

where δ_i is the same price coefficient as in equation (4) and η_{ij}^- measures utility change other than monetary loss. For example, when loss occurs, the consumer will not be refunded for the monetary loss. Additionally, she or he would need to spend money on produce elsewhere to fulfill their weekly needs, which leads to extra cost (utility deduction) in time, transportation, and grocery consumption.

Similarly, in case of good harvest, when the consumer receives extra produce with an additional monetary value of p_{js}^+, the utility index of gain y_{ijs}^+ that consumer i gets from purchasing CSA share option j in scenario s is

$$y_{ijs}^+ = \eta_{ij}^+ + p_{js}^+ \delta_i, \tag{3}$$

where η_{ij}^+ captures additional utility increase other than monetary benefits, such as utility obtained from consuming extra produce.

We assume that the reference point is equivalent to one's current assets. In our CSA participation experiment, a consumer who chooses a CSA option expects the current asset to be equal to the up-front payment associated with the chosen option, so he or she will compare the final asset (received value of chosen CSA) with the current asset (up-front payment of chosen CSA) to assess the payoff of the product. Following Tversky and Kahneman (1992) and other empirical studies (Tanaka, Camerer, and Nguyen, 2010; Jindal, 2015), the value function is constructed by a two-part power functional form given by[4]

$$v(y_{ijs}^k) = \begin{cases} (y_{ijs}^k)^{\alpha_i}; & y_{ijs}^k \geq 0 \\ -\lambda_i(-y_{ijs}^k)^{\alpha_i}; & y_{ijs}^k < 0 \end{cases} \tag{4}$$

Noindent In this functional form, k is the utility index $k \in \{\pm, -, +\}$, $\alpha_i > 0$ represents the concavity of utility curvature for gains,[5] and $\lambda_i > 0$ measures the degree of loss aversion. If the subject is more sensitive to loss than to gain, $\lambda_i > 1$, otherwise $0 < \lambda_i < 1$.

In EUT, the utility of an uncertain prospect is the sum of outcome utility weighted by probability (Tversky and Kahneman, 1992), but in CPT, the utility of each outcome should be multiplied by a decision weight instead of the actual probability. To capture the systematic distortion over risk probabilities, we adopt a single parameter form for the probability-weighting function:[6]

$$w_i(\pi_{js}) = \frac{\pi_{js}^{\mu_i}}{\left(\pi_{js}^{\mu_i} + (1-\pi_{js})^{\mu_i}\right)^{\frac{1}{\mu_i}}}, \tag{5}$$

[4] Kahneman and Tversky (1979) first used a value function to show the existence of gain and loss separated by a reference point and to differentiate the value function in prospect theory from the utility function in expected utility theory, where the outcome state is entirely defined by the functional form.

[5] In EUT, under the same functional form, α_i controls the level of risk preference, $\alpha_i < 1$ indicates risk aversion, $\alpha_i = 1$ is risk neutral, and $\alpha_i > 1$ indicates risk seeking. However, under the CPT specification, α_i only reflects the curvature of the value function; risk preference is determined by a joint effect of risk curvature, loss aversion, and probability weighting.

[6] Prelec (1998) proposes another, widely adopted probability-weighting function: $w_i(\pi_{js}) = \exp[-(-\ln \pi_{js})^{\mu_i}]$. However, studies have shown no significant differences in risk-parameter estimates using both forms of weighting function (Gonzalez and Wu, 1999; Jindal, 2015). Similar results have also been found in our study.

where π_{js} is the probability of loss/gain for option j in scenario s, and μ_i is the individual-specific weighting parameter to be estimated.

Prospect Theory Utility

Jointly using the specifications of utility index y_{ijs}^{c}, value function $v(\cdot)$, and probability-weighting function $\omega(\cdot)$, we can define the CPT utility. In the case of possible loss, we set the value of certain loss to be $v(y_{ijs}|loss) = v(y_{ijs}^{\pm}) - v(y_{ijs}^{-})$, indicating the final value is equal to the deterministic consumption utility minus utility deduction due to loss. Thus, the CPT utility that consumer i gets from purchasing CSA share option j in scenario s under possible loss is

$$(6) \quad PU_{ijs}^{-} = w_i^{-}(\pi_{js})\, v(y_{ijs}|loss) + \left[1 - w_{js}^{-}(\pi_{js})\right] v\left(y_{ijs}^{pm}\right) + \varepsilon_{ijs}^{-} = v_{i,-}^{*}\left(\boldsymbol{x}_{js},\ p_{js}^{-},\ \pi_{js}\right) + \varepsilon_{ijs}^{-}.$$

Similarly, define $v(y_{ijs}|gain) = v(y_{ijs}^{\pm}) + v(y_{ijs}^{+})$. Then, in the circumstance of possible gain, the CPT utility PU_{ijs}^{+} can be derived as

$$(7) \quad PU_{ijs}^{+} = v_{i,+}^{*}\left(\boldsymbol{x}_{js},\ p_{js}^{+},\ \pi_{js}\right) + \varepsilon_{ijs}^{+},$$

where $w_i(\pi_{js})$ is the weighted probability consumer i gets from purchasing CSA share option j in scenario s and ε_{ijs} is the random utility error. If the respondent chooses to opt out, then his or her CPT utility, PU_{ijs}^{0}, equals ε_{ijs}^{0}. With this model specification, we can easily test the model's goodness of fit by estimating loss aversion only (risk curvature equals 1), risk only (loss aversion equals 1), and the probability-weighting-free models and compare them to the full CPT model and EUT model.

Assuming the error term ε_{ijs} to be type I extreme value distributed, consumer i chooses CSA option j in scenario s if and only if

$$(8) \quad v_{i,+/-}^{*}\left(\boldsymbol{x}_{js}, p_{js}^{+/-}, \pi_{js}\right) + \varepsilon_{ijs}^{+/-} \geq v_{i,+/-}^{*}\left(\boldsymbol{x}_{j's}, p_{j's}^{+/-}, \pi_{j's}\right) + \varepsilon_{ij's}^{+/-},$$

where $j,\ j' \in J$, and $j \neq j'$. Implementing a multinomial logit model, the probability that consumer i chooses option j in scenario s is characterized as

$$(9) \quad \Pr\left\{D_{ijs}^{+/-} = 1\right\} = \frac{\exp\left(v_{i,+/-}^{*}\left(\boldsymbol{x}_{js},\ p_{js}^{+/-},\ \pi_{js}\right)\right)}{1 + \sum_{j' \in J} \exp\left(v_{i,+/i}^{*}\left(\boldsymbol{x}_{i,+/-},\ p_{js}^{+/-},\ \pi_{js}\right)\right)}$$

and $D_{ijs}^{+/-} = 1$ when consumer i chooses option j in scenario s.

We use the Bayesian method to estimate individual preference parameters $\theta_i = (d_{ijs}, \beta_i, \gamma_i, \delta_i, \sigma_i, \rho_i, \rho_i)$.[7] A hybrid Markov chain Monte Carlo (MCMC) algorithm with normal heterogeneity distribution $\theta_i \sim N(\Delta' z_i, V_\theta)$ was adopted, where the mean of the random effects distribution is dependent on the values of the demographic variables, z_i, and the estimated matrix of coefficients, Δ. Set the priors distribution as

$$(10) \quad \mathrm{vec}(\Delta | V_\theta) \sim N\left(\mathrm{vec}\left(\bar{\Delta}\right), A^{-1} \otimes V_\theta\right).$$

The prior on the covariance matrix is

$$(11) \quad V_\theta \sim IW(v, V_0),$$

where the second-stage priors are set to be diffuse and the Wishart is set to have expectation I with very small degrees of freedom, such that $v = \dim(\theta_i) + 3$. Thus, estimates of θ_i can be obtained

[7] Following Jindal (2015), risk curvature and probability-weighting parameters are exponentially transformed, $\alpha_i = \exp(\sigma_i)$ and $\mu_i = \exp(\rho_i)$, to ensure that they are monotonically increasing.

with an MCMC approach with a random walk Metropolis–Hastings step.[8] Further details of the specification can be found in Rossi, Allenby, and McCulloch (2005), and we modified the bayesm package (Rossi, 2015) in R (R Core Team, 2016) to conduct our analysis.

Results

A nationwide online survey was distributed through Qualtrics™ in January 2017. Complete and valid responses were collected from 470 respondents. Table 2 summarizes respondents' sociodemographic characteristics. Respondents' average age was 52 years, the average level of the highest education was some college or associate degree, and average household income was \$35,001–\$50,000. Most respondents were married (77%), Caucasian (90%), and female (69%). About 11% of them had kids under 12 years old, and 18% were unemployed. Regarding CSA, 44% of respondents stated that they were familiar with CSA, and 5% had experience with or were subscribing CSA. The target audience of our survey is the family member who is responsible for grocery shopping and is familiar with or at least understands CSA subscription. In such case, a nationally representative sample is not required, especially given the fact the knowledge-screening question will directly exclude those who are not familiar with the CSA subscription. Therefore, our sample is noticeably different from the U.S. census, having a higher percentage of females, a higher percentage identifying as white, and older in age.

Initial Analysis Using Reduced-Form Model

We first adopt a mixed logit model to provide a baseline understanding of preferences using a reduced form of the full model. Table 3 summarizes the estimation results of our two models, which vary in their combinations of explanatory variables. Model 1 tests CSA attributes, up-front payments,[9] and outcome uncertainty (product of probability and loss/gain value); model 2 modifies the outcome uncertainty variable by introducing the second and third orders of probabilities.

The estimated coefficients of the variables in both models are statistically significant at the 0.1% level. Product attributes—including a good variety of produce (11–15 varieties compared to 6–10 varieties) and low distance to pick-up place (5 miles compared to 10 miles)—are substantially valued. Significant negative impacts are also found for up-front payment, meaning consumers are significantly sensitive to price. The coefficients for the interactive terms of probability and gain/loss in model 1 indicate that consumers strongly prefer a possible increase in the final value of CSA subscription box but are substantially sensitive to possible loss. Last, the coefficients of the higher orders of probability in model 2 indicate that probability's impact on consumer choice is nonlinear; probability weighting in CPT may remedy this distortion.

Estimation Results under CPT and EUT Frameworks

The full sample contains 33,840 choice observations, with 16,920 for the possible loss model and 16,920 for the possible gain model. We performed 100,000 MCMC simulations, and every 20th draw was retained for analysis. It is essential to note that in the Bayesian analysis, the draws converge in distribution to the posterior distribution of the model parameters, in contrast to other forms of estimations (e.g., maximum likelihood), which converge to a point (Rossi, Allenby, and McCulloch, 2005). Figure 2 shows the density of posterior distribution for taste parameters of the full model. By allowing heterogeneity, each respondent has his or her individual-specific estimates. Table 4 reports the model estimates for the full sample under CPT and EUT frameworks. The reported indices include the posterior population mean, standard deviation, 5% and 95% credible interval (C.I.).

[8] For further Bayesian estimation details, refer to Rossi, Allenby, and McCulloch (2005, chapter 5).
[9] For ease of comparison, we rescaled the range of possible losses/gains to $[-1, 1]$ throughout the analysis, so the price level is accordingly rescaled to $[0, 4]$.

Table 2. Statistical Summary of Sociodemographics for the Sample Respondents (N = 470)

Demographic Characteristics	Explanation	Mean (Std. Dev.)
Age	Age of respondents:	4.19
	1. ≤ 30	(1.42)
	2. 31–40 years old	
	3. 41–50 years old	
	4. 51–60 years old	
	5. 61–70 years old	
	6. > 70	
Education	Highest level of education completed:	3.74
	1. Some high school or less	(1.64)
	2. High school diploma or equivalent	
	3. Some college	
	4. Associate degree	
	5. College diploma	
	6. Some graduate school	
	7. Graduate/professionals degree	
Income	Total family income earned in previous year:	4.04
	1. ≤ $15,000	(2.18)
	2. $15,001–$25,000	
	3. $25,001–$35,000	
	4. $35,001–$50,000	
	5. $50,001–$65,000	
	6. $65,001–$80,000	
	7. $80,001–$100,000	
	8. $100,001–$150,000	
	9. > $150,000	
Household size	Number of people live in household	2.26
		(1.19)
Total duration	Average time to complete the survey (in seconds)	987
		(778)
		Percentage
Male	Male respondents (%)	31
Married	Married respondents (%)	77
Kid	Have a kid under 12 years old (%)	11
White	Race identified as white (%)	90
Unemployed	Unemployed respondents (%)	18
CSA member	Respondents who subscribed to CSA previously (%)	5
Not Familiar	Respondents who indicated they were not familiar with CSA (%)	56

Notes: Numbers in parentheses are standard deviations.

The results for both models allow us to identify a significant coefficient for the CSA-specific constant. This may indicate that (apart from price, variety, and distance), consumers are generally in favor of participating in CSA programs rather than opting out, possibly because of the utility obtained from supporting the local community, having fresh and healthy food, knowing the source

Table 3. Reduced-Form Estimation Results from Mixed Logit Analysis (*N* = 33,840)

Variables	Model 1	Model 2
CSA	2.50****	2.89****
	(0.11)	(0.11)
Good variety	0.60****	0.65****
	(0.05)	(0.05)
Low distance	0.28****	0.38****
	(0.04)	(0.05)
Price	−0.58****	−0.71****
	(0.03)	(0.04)
$\pi p^{+/-}$	3.31****	−6.70****
	(0.15)	(0.43)
$\pi^2 p^{+/-}$		28.72****
		(1.57)
$\pi^3 p^{+/-}$		−16.26****
		(0.32)
Log-likelihood	−10,935	−10,335
χ^2 test	0.00	0.00

Notes: Four asterisks (****) indicate significance at the 0.1% level. Numbers in parentheses are standard errors.

Table 4. Estimation Results for Prospect Theory Model and Expected Utility Model

Variable	Population Mean	Population Std. Dev.	5% Credibility Interval	95% Credibility Interval
Cumulative prospect theory (CPT) model				
CSA (c)	8.69	0.48	7.98	9.56
Price (δ)	1.85	0.10	1.70	2.02
Variety (β)	1.55	0.09	1.41	1.70
Distance (γ)	0.78	0.08	0.65	0.89
Probability weight (μ)	1.22	0.05	1.13	1.31
Risk curvature (α)	0.79	0.03	0.74	0.84
Loss aversion (λ)	1.71	0.14	1.52	1.94
Risk intercept (η)	−0.31	0.24	−0.69	0.07
Log marginal density (MD)	−6,749.00			
Trimmed log MD	−6,705.56			
Expected utility (EUT) model				
CSA (c)	5.50	0.17	5.22	5.77
Price (δ)	1.10	0.05	1.01	1.18
Variety (β)	0.96	0.04	0.89	1.02
Distance (γ)	0.46	0.04	0.39	0.53
Risk curvature (α)	0.62	0.26	0.27	1.22
Risk intercept (η)	−1.48	0.11	−1.67	−1.30
Log marginal density (MD)	−7,181.40			
Trimmed log MD	−7,130.53			

Notes: In-sample goodness of fit is measured by the log marginal density calculated using Newton and Raftery's (1994) sampling method.

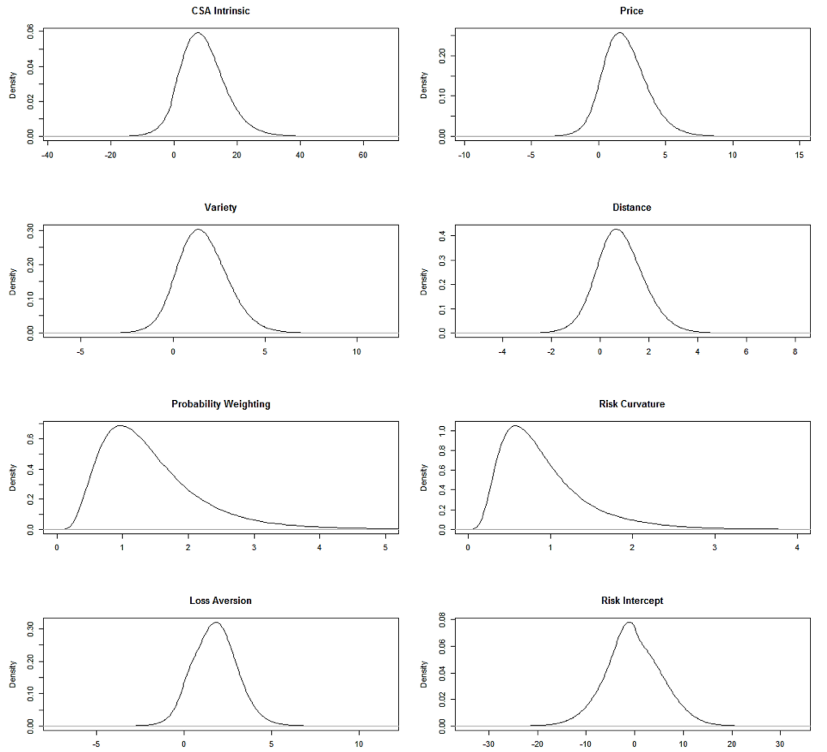


Figure 2. Posterior Distribution of Heterogeneity for Full Prospect Theory Model

and production practice of the produce, or environmental protection. Comparing product attributes, we find price (unit decrease of \$150) to be the most important factor affecting respondents' decisions, followed by a good variety of produce (11–14 varieties compared to 6–10 varieties) and a short distance to the pick-up location (5 miles compared to 10 miles). For the risk parameters, the population mean of risk curvature is estimated to be steeper in the EUT framework (0.62) than in the CPT framework (0.79). This is consistent with prior empirical estimates of 0.5–1.0 (e.g., Tversky and Kahneman, 1992; Wu and Gonzalez, 1996; Donkers, Melenberg, and Van Soest, 2001). The CPT model has an estimated loss aversion parameter of 1.71, indicating mild loss aversion when loss and gain are both possible. The probability-weighting parameter is estimated to be 1.22, representing an S-shaped probability-weighting function. We further compare the models' goodness of fit with varied model specifications, using log marginal density and trimmed log marginal density (removing lower and upper 2% outliers) to measure the comparative goodness of fit for each model specification.[10] Both indices suggest that the CPT model—which takes full account of probability weighting, risk curvature, and loss aversion—has better goodness of fit than the EUT model.[11]

Estimation Results under Loss and Gain Domains

Table 5 presents the CPT model results in both loss and gain domains. For CSA attributes, similar rankings are observed in the gain and loss models, consistent with the results for the full domain.

[10] The log marginal density is computed using the Newton–Raftery (1994) approximation.

[11] We also compared the models' goodness of fit with varied model specifications, including the loss-free model ($\lambda = 1$), curvature-free model ($\alpha = 1$), and weighting-free model ($\mu = 1$). Our results show that the prospect theory model has the best goodness of fit among all model specifications and EUT model has the lowest goodness of fit index. Additionally, for risk-parameter specifications, weighting-free model has the lowest goodness of fit, followed by the curvature-free model. The loss-free model leads to the smallest decrease in log marginal density.

Table 5. Prospect Theory Model Estimation Results under Possible Loss and Possible Gain (N = 16,920)

Variable	Population Mean	Population Std. Dev.	5% Credibility Interval	95% Credibility Interval
Possible loss model				
CSA (c)	12.89	0.5	12.17	13.8
Price (δ)	1.98	0.16	1.68	2.22
Variety (β)	2.81	0.3	2.29	3.3
Distance (γ)	1.34	0.2	1.03	1.73
Probability weight (μ)	1.34	0.09	1.19	1.49
Risk curvature (α)	0.51	0.03	0.47	0.56
Loss aversion (λ)	2.29	0.1	2.15	2.48
Risk intercept (η)	7.31	0.29	6.8	7.79
Log marginal density	$-3,637.13$			
Trimmed log marginal density	$-3,587.67$			
Possible gain model				
CSA (c)	6.56	0.56	5.73	7.62
Price (δ)	2.06	0.16	1.82	2.34
Variety (β)	1.45	0.09	1.31	1.62
Distance (γ)	0.5	0.1	0.35	0.66
Probability weight (μ)	0.67	0.06	0.59	0.78
Risk curvature (α)	0.98	0.06	0.88	1.07
Loss aversion (λ)	0.84	0.14	0.63	1.12
Risk intercept (η)	7.39	0.67	6.18	8.57
Log marginal density	$-3,323.16$			
Trimmed log marginal density	$-3,270.26$			

However, the magnitude of the coefficients for variety and distance are higher in the possible loss model compared to those in the possible gain models. This is reasonable because product attributes need to generate more value to offset the utility deduction of possible loss due to poor harvest.

Risk curvatures are estimated to be 0.51 and 0.98 for the loss model and the gain model, respectively. Further comparing the distribution of population mean for risk curvatures between the loss/gain models and the full domain CPT model in Figure 3, it is obvious that the average utility curvature for the gain model is closer to linearity ($\alpha = 1$). This is reasonable because risk is minimized under the circumstance that only gain would occur, and substantial heterogeneity within risk curvature estimates is also observed for the gain model. On the other hand, utility curvature under possible loss circumstance is extremely concave, around 0.5, and the CPT model under the full domain neutralizes both curvature levels. The difference in risk curvatures between the loss and gain models demonstrates that respondents' sensitivity is more diminishing toward possible loss than toward possible gain.

Figure 4 demonstrates the distribution of population mean for loss aversion parameter (λ) and the 90% credible interval among the possible loss, possible gain, and full domain CPT models. Reasonably, loss aversion has the most impact in the loss model (2.31), consistent with findings by Tversky and Kahneman (1992) and Bocquého, Jacquet, and Reynaud (2014), who reported λ of around 2.29. Other studies have identified a wide range of values (1.07–3.2) for loss aversion (e.g., Andersen, Harrison, and Rutström, 2006; Abdellaoui, Bleichrodt, and Paraschiv, 2007). Such

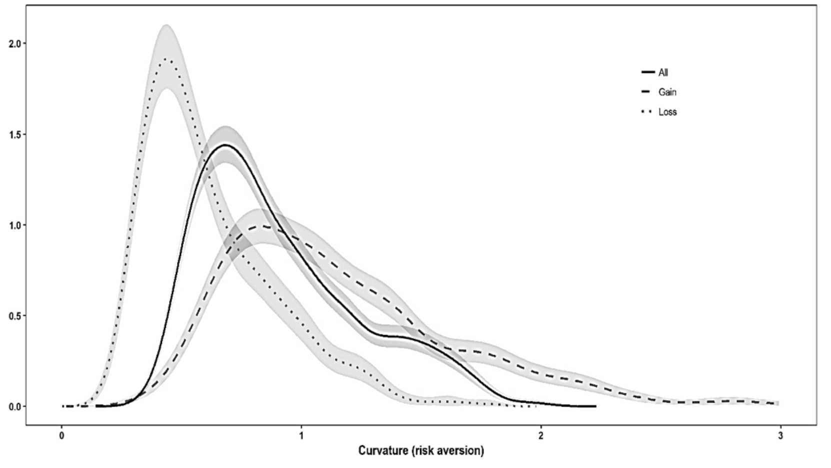


Figure 3. Compare Heterogeneous Population Mean and 90% Credibility Region of Risk Curvature (α) for Full Prospect Theory Model, Possible Loss Model, and Possible Gain Model

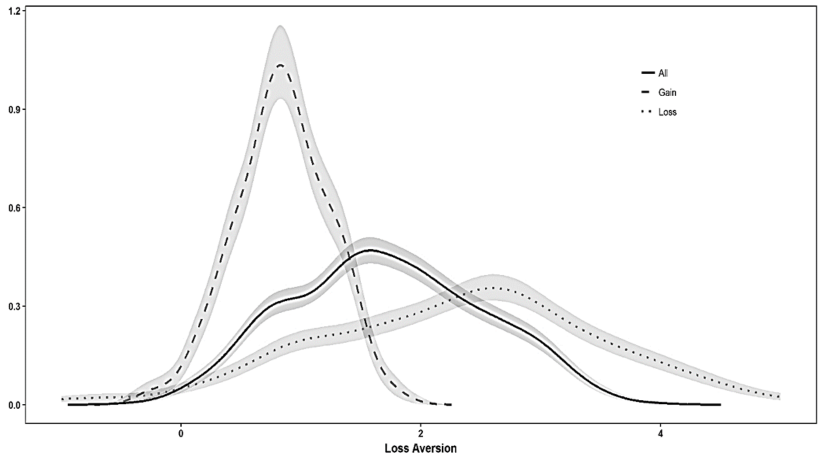


Figure 4. Compare Heterogeneous Population Mean and 90% Credibility Region of Loss Aversion (λ) for Full Prospect Theory Model, Possible Loss Model, and Possible Gain Model

variation is also reflected by the significant heterogeneity for the loss model estimates shown in Figure 4.

The probability-weighting parameter in the gain model is 0.67, showing an inverse S-shaped probability distortion in the circumstance of possible gain. However, probability weighting is estimated to be greater than 1 in the loss model, indicating an S-shaped weighting function. While S-shaped probability weighting is in line with Jindal (2015), such a functional shape opposes most prior prospect theory studies, in which the parameter ranges between 0.5 to 1 with inverse S-shaped weighting functions (e.g., Tversky and Kahneman, 1992; Booij and van de Kuilen, 2009; Tanaka, Camerer, and Nguyen, 2010). There are two possible explanations. First, the risk attributes in our design of possible gain choice scenarios are identical to the lottery experiment in which respondents choose between possible monetary gains. However, when individuals face the reverse scenarios of possible loss, they also reverse probability distortion pattern to underweight low probabilities and overweight medium-to-high probabilities of loss rather than overweighing low probabilities.

Especially in the case of purchasing CSA shares, consumers may neglect very low risk of loss while being extremely reluctant to purchase if there is medium or large probability of loss.

The risk intercepts for possible loss and gain are significant and have similar magnitudes (7.31 and 7.39), indicating substantial nonmonetary utility change upon the occurrence of loss or gain. In case of loss, the decrease in nonmonetary utility represents the extra cost in time, transportation, and grocery consumption to offset loss in CSA subscription, and the nonmonetary utility increase in gain circumstance reflects the value and potential use of bonus produce. For the full domain CPT model, the risk intercepts of loss and gain models offset each other and result in a slightly negative value (−0.31).

Consumer Sociodemographics' Impact on Risk Preferences

Sociodemographic variables were mean-centered, so the mean of random effects distribution can be interpreted as the average respondent's part worths (Rossi, Allenby, and McCulloch, 2005). Table 6 summarizes the posterior means and standard deviations of demographic variable coefficients.

Regarding familiarity and experience with CSA, those who indicated being unfamiliar with CSA generally place higher values on product attributes; they are also more risk averse, with steeper risk curvature and stronger loss aversion relative to respondents who had some knowledge of CSA. Compared to participants with less CSA experience, those who had subscribed to CSA programs place higher values on variety and distance, indicating these two attributes are more important for existing CSA purchasers. Meanwhile, they care less about price and possible loss than people who have not previously purchased CSA shares.

Consumers with a stronger preference for purchasing CSA shares tend to be older and more educated, with higher income and larger households, consistent with findings by Lang (2005) and Vassalos, Gao, and Zhang (2016). Meanwhile, increases in age, education, and household size also lead to higher price sensitivity. Interestingly, being married, retired, or having kids negatively affects the utility of purchasing CSA shares, but these respondents are also less price sensitive, possibly because of their unwillingness to change from their status quos and reluctance to accept CSA as a new way of grocery shopping. With respect to people's risk preferences, we find that being retired, white, or male and having children all contribute to decreased loss aversion, while participants who are older, female, married or having a larger family are more loss averse. Last, CSA nonmonetary utility would decrease if the final perceived value becomes lower than the up-front payment value, unless the respondent had subscribed CSA before or had a higher income level.

Market Sensitivity Analysis

Given the results from both CPT and EUT estimations, we conduct a market sensitivity analysis with the variation of both CSA price and possible gain/loss. Assuming a representative 20-week CSA operation that offers a good product variety and 5 miles distance to the pick-up location, along with a fixed percentage of 20% for the occurrence of possible loss/gain, we calculate the market share as the percentage of the sample population who are willing to participate in CSA under certain combination levels of price and gain/loss value. Figure 5 shows the three-dimensional surface plots of market-share sensitivity comparison between the CPT and EUT frameworks; the price of CSA subscription service ranges from \$300 to \$750, and gain/loss value is set to be in a reasonable range of −\$150 to \$150.

The four graphs in Figure 5 show different angles of the market share three-dimensional surface. Figures 4(a) and 4(b) present the incremental angle and decremental angle of price and gain/loss, respectively. Starting from the combination of low price (\$300) and large possible loss (−\$150), the market share under EUT framework is estimated to be around 75%, significantly higher than the market share of 41% under CPT framework, largely due to the disutility of possible loss generated from people's loss aversion and probability weighting. The discrepancy of market share between

Table 6. Posterior Mean and Standard Deviation of Sociodemographic Effect

Demographics	c	δ	β	γ	$\ln(\mu)$	$\ln(\alpha)$	λ	η
Intercept	8.68	1.85	1.55	0.78	0.20	−0.24	1.71	−0.31
	(0.49)	(0.11)	(0.09)	(0.08)	(0.05)	(0.04)	(0.14)	(0.31)
Not familiar	1.04	0.25	0.34	0.14	−0.13	−0.06	0.11	−0.21
	(0.67)	(0.19)	(0.16)	(0.18)	(0.08)	(0.06)	(0.14)	(0.53)
Subscribed	−0.79	−0.61	0.45	0.20	0.02	0.09	−0.36	0.10
	(1.75)	(0.41)	(0.39)	(0.31)	(0.23)	(0.14)	(0.40)	(1.34)
Age	0.89	0.22	0.15	0.10	0.06	0.01	0.09	−0.13
	(0.34)	(0.09)	(0.08)	(0.08)	(0.04)	(0.03)	(0.08)	(0.26)
Male	0.38	−0.01	−0.02	0.02	0.07	−0.08	−0.15	−0.77
	(0.70)	(0.20)	(0.17)	(0.15)	(0.09)	(0.07)	(0.22)	(0.63)
Education	0.10	0.07	0.07	0.07	0.03	−0.02	0.01	−0.12
	(0.21)	(0.05)	(0.05)	(0.04)	(0.03)	(0.02)	(0.07)	(0.20)
Married	−1.32	−0.38	−0.23	−0.14	0.13	0.00	0.13	−0.35
	(0.99)	(0.25)	(0.22)	(0.19)	(0.10)	(0.08)	(0.26)	(0.73)
Kid	−1.55	−0.51	−0.02	−0.18	−0.46	0.17	−0.32	−0.27
	(1.46)	(0.35)	(0.36)	(0.27)	(0.18)	(0.13)	(0.43)	(1.21)
Household size	0.46	0.05	0.09	0.03	0.06	0.00	0.03	−0.28
	(0.42)	(0.10)	(0.09)	(0.08)	(0.05)	(0.03)	(0.10)	(0.29)
White	0.42	0.47	0.18	0.25	0.00	0.16	−0.81	−1.46
	(1.34)	(0.34)	(0.29)	(0.28)	(0.14)	(0.11)	(0.38)	(0.91)
Income	0.10	−0.02	0.00	−0.01	−0.04	0.00	0.04	0.15
	(0.21)	(0.05)	(0.05)	(0.04)	(0.02)	(0.02)	(0.04)	(0.13)
Retired	−1.06	−0.18	0.07	−0.13	0.04	0.03	−0.31	−0.02
	(0.84)	(0.23)	(0.23)	(0.16)	(0.10)	(0.08)	(0.22)	(0.64)

Notes: Sociodemographic variables were mean-centered before the analysis, so the mean of random effects distribution can be interpreted as the average respondent's part worths.

EUT and CPT gradually diminishes with the increase in both CSA price and possible value change in received product and becomes indifferent at the surface area. At the point at which price reaches higher than \$700 and no possible loss could occur, the market shares under CPT shift higher than those under the EUT framework. This reduced market share discrepancy can be largely explained by the stronger price effect and lower possible gain/loss effect for the EUT model compared to the CPT model. Specifically, from the price angle in Figure 4(c), it is obvious that (conditional on a fixed gain/loss value) market share under EUT significantly and increasingly reduced by about 25% when the CSA price increases from \$300 to \$750, while the change of market share was around 4% for CPT model. Galt (2013) explained consumers' insensitivity toward CSA price from the perspective of the original CSA concept, as consumers prioritize the added value of CSA (e.g., the well-being of farmers) over their economic interest, and the price is not the consumers' sole consideration. From the perspective of possible gain/loss exhibited in Figure 5d, market share under CPT becomes more

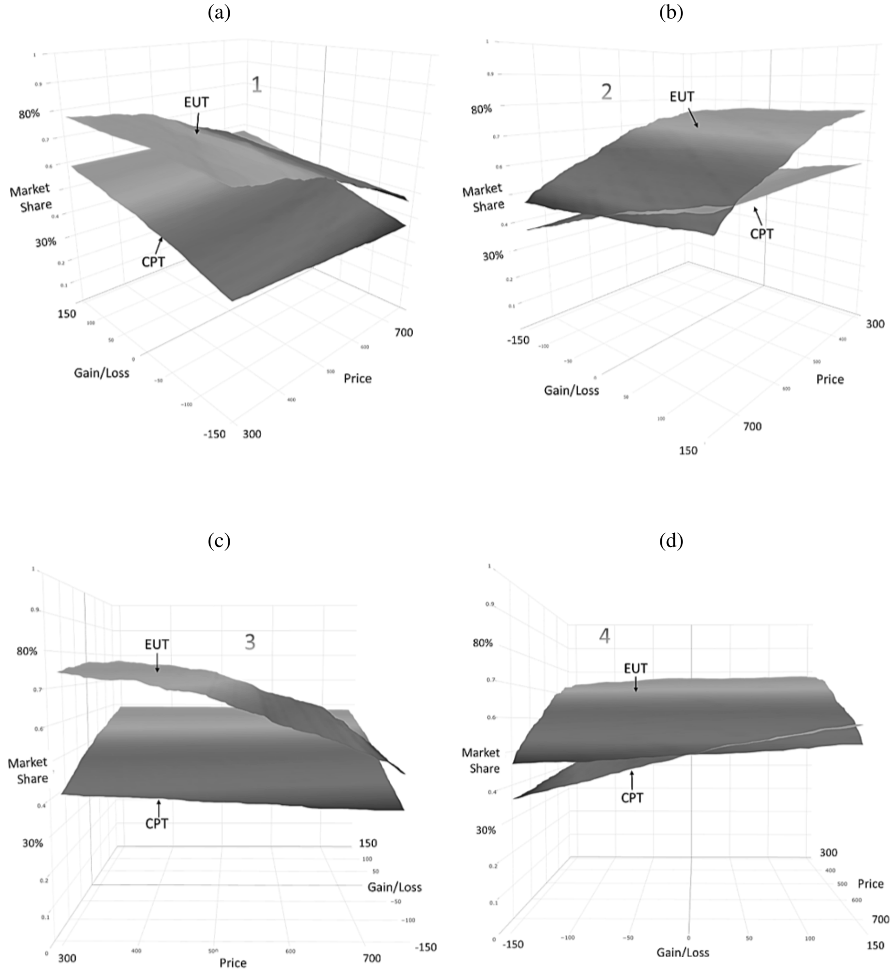


Figure 5. Market Share Sensitivity Comparison between EUT Model and CPT Model in Response to Changes in CSA Price and Possible Gain/Loss

Notes: Figures 5a and 5b show the incremental angle and decremental angle of price and gain/loss, respectively, Figure 5c indicates the pricing sensitivity effect and Figure 5d indicates gain/loss sensitivity effect.

sensitive. For example, given a change from a \$150 loss to a \$150 bonus produce in the final received product, the EUT model slightly increased the market share from 47% to 52% under a fixed price of \$750, but the CPT model predicts a significant increase in market share (from 37% to 58%), where it surpasses the level of EUT market share at around \$5 in loss. Meanwhile, with the loss-aversion effect, we also observe that the marginal rate of increase in market share is relatively higher in the loss domain than in the gain domain.

Discussion and Conclusions

Under the cumulative prospect theory (CPT) framework, we investigate consumers' community-supported agriculture (CSA) participation under risk and uncertainty using discrete choice experiments (DCE) with flexible reference points. We find that when making decisions about CSA participation, consumers tend to be risk seeking for low probabilities of bonus produce or loss and risk averse for medium-to-high probabilities of loss or gain. Under the same size of loss and gain, consumers are more sensitive to loss than to gain. Therefore, we conclude that risk preferences in CPT—namely reference dependence, loss aversion, diminishing sensitivity and probability weighting—significantly affect consumers' decision to participate in CSA.

In response to the reference-dependent preference, CSA suppliers need to be careful when deciding subscription prices because consumers will refer to the up-front price as a reference of initial wealth output and weight the final value of products with respect to the reference value to determine whether they receive a gain or loss. In the case of good harvest, most farmers choose to market extra produce through farmers' market or other local outlets or donate to local food banks (Woods et al., 2009). Results of diminishing sensitivity imply that farmers should consider gifting bonus produce worth up to 30% of the up-front value to subscribers to achieve the maximum utility increase. However, presenting too much bonus to CSA consumers will lead to a diminished utility increase once the maximized utility change in gain is reached. Similarly, in a loss situation due to poor harvest (unexpected weather, pest or resource shortage, etc.), farmers should try to make up the small loss for consumers, particularly under the significant loss aversion. But if the loss is substantial, a small offset would not comfort consumers significantly due to their diminished sensitivity in loss.

Our results also shed light on the implications of marketing CSA to potential customers. Since this risk information cannot be withheld in CSA marketing (and the risk of loss is a major drawback for CSA participation), operators could counter the negative effect of possible loss by emphasizing the farm's good production history with bonus produce (if possible), even if there is only a small possibility of getting limited production surplus. Consumers tend to overweight low probabilities in the gain domain and are mostly risk averse for bonus produce. Meanwhile, CSA attributes should be fully explained as consumers strongly prefer an increased variety of fresh produce with a willingness to pay of \$6.28/week to improve CSA variety from fair (6âĂŤ10) to good (11–15);[12] they are also willing to pay \$3.16/week for a pick-up location 5 miles rather than 10 miles away. Last, given the significant coefficient for CSA-specific constant, farmers should highlight CSA benefits (apart from weekly fresh produce), which include but are not limited to supporting local farmers, involving in local communities, and contributing to sustainability and environmental protection. In line with Lang (2005) and Pole and Kumar (2015), our study reaffirms the sociodemographic background of targeted CSA consumers, who tend to be older, Caucasian, affluent, and more educated. One limitation of this study in understanding the CSA customer profile is the lack of geographic indicators. It would be informative to estimate whether preference variations correspond to different states or regions.

Further sensitivity analysis suggests that market share responds differently to the CPT and EUT frameworks. Using the estimation results from the EUT model, CSA market share is dominated by the changes in subscription price and relatively insensitive to changes in possible gain/loss. However, after controlling for all risk parameters under the CPT framework, market share becomes primarily controlled by possible gain/loss instead of CSA price. As CPT comprehensively captures consumer risk preference in decision making, the sensitivity results of market share reemphasize the importance of risk mitigation for CSA operations. As a result, we conclude that while CSA, as an alternative farming system, transfers production risk partially to its members, this transferred part of risk, in return, becomes the determinant of CSA market share. Given the lack of single-crop insurance policies for many vegetables and fruits (Robinson, Marlow, and Madeley, 2013) and the large impact of spatial shocks on small and geographically dispersed farms such as CSA programs (Ligon, 2011), operators should carry out essential practices to avoid risk and address uncertainty during the growing season. For example, high tunnel systems could help operators improve plant health and quality, reduce energy use, and extend the growing season. The USDA has recently acknowledged the benefits of high tunnel practices and promoted the High Tunnel System Initiative to provide producers with financial and technical support (U.S. Department of Agriculture, 2015). Additionally, the Federal Crop Insurance Act has implemented the Whole-Farm Revenue

[12] The willingness to pay value is calculated using the common approach of dividing attribute coefficient by price coefficient (see Yue, Zhao, and Kuzma, 2015, for an example).

Protection plan in the 2015 crop year, providing a risk-management safety net for all crops on the farm, regardless of varieties (U.S. Department of Agriculture, 2017). Overall, CSA operators should take advantage of the available risk-reduction tools to ensure loss-free production for risk-sensitive consumers.

The full CPT model fits our data significantly better than does the EUT model. From the CPT results, we find further evidence of systematically distorted probability perceptions, indicating that consumers may hold subjective beliefs toward the information they receive (Lusk, Schroeder, and Tonsor, 2014). In the meantime, it is also possible that belief could affect consumer choices of CSA in the choice experiment. By not choosing a CSA option, consumers may indicate that they do not prefer the specific CSA profile and associated price or consumers may simply not believe that CSA could deliver the proposed attributes at that price. Future research should incorporate belief measurement with Likert scales to back up the elicitation of attribute preferences.

Future research could also test reference point effects. A commonly accepted solution for reference points is using respondents' expectations (Kőszegi and Rabin, 2006, 2007; Ericson and Fuster, 2011). In this study, we assume consumers' expectation for CSA is the choice-specific up-front payment, which can be interpreted as the current asset. However, consumers' expectations for the final value of CSA could fluctuate around the up-front payment based on personal experience, information perception, and household background. Future consumer studies of CSA that incorporate uncertain outcomes should investigate the variation in reference points based on differing expectations.

Meanwhile, as the uncertain outcome occurs after the up-front payment is made, the discrepancy between when consumers invest their current asset and when they realize a possible loss or gain in the final asset could cause time and hyperbolic discounting effects. Even though this time-discounting effect is minimized under our survey design (as respondents make simultaneous choices for both current product and final product condition), it would be interesting for future research to define valid functional forms to elicit consumers' time preferences for CSA or for any product with future uncertainty.

Finally, a recent study by Apesteguia and Ballester (2018) proves that using a random utility model in risk elicitation experiments violates preference monotonicity, which is also a valid concern for our study as the risk attributes are design based on nested pairs of gamble-like uncertain outcomes. The use of Bayesian methods in this study may avoid protentional nonmonotonicity problems,[13] but future studies should pay special attention to the identification of risk preferences with random utility models. Overall, as one of the first attempts to study consumer preference for nonmonetary products under risk and uncertainty, the results of this study set up an initial baseline with multiple future directions that could lead to fruitful explorations. We believe the DCE method under CPT framework can be applied to a wider range of preference elicitations, such as insurance, subscription services, vacation destinations, and environmental policy.

[First submitted December 2018; accepted for publication May 2019.]

[13] Apesteguia and Ballester (2018) fixed the violation of monotone preference using random parameter model with a tremble parameter that addresses stochastic dominance. In this study, our use of the Bayesian method may have partially prevented nonmonotonicity in that each parameter is also randomly identified under a fixed prior range.

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